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Tripathi et al.

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(54) ONE MODEL UNIFYING STREAMING AND NON-STREAMING SPEECH RECOGNITION

(71) Applicant: **Google LLC**, Mountain View, CA (US)

(72) Inventors: **Anshuman Tripathi**, Mountain View, CA (US); **Hasim Sak**, Santa Clara, CA (US); **Han Lu**, Redmond, WA (US); **Qian Zhang**, Mountain View, CA (US); **Jaeyoung Kim**, Cupertino, CA (US)

(73) Assignee: **Google LLC**, Mountain View, CA (US)

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G06N 3/04	(2023.01)

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(58) **Field of Classification Search**

CPC G06N 3/04; G06N 3/088

See application file for complete search history.

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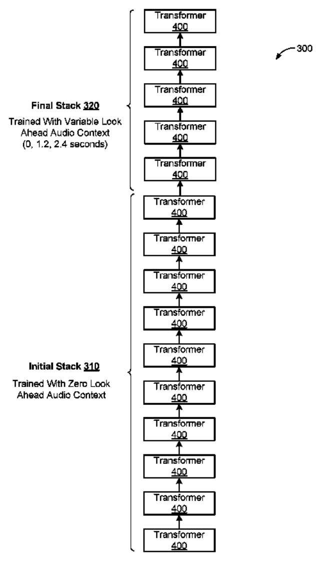
Primary Examiner — Jesse S Pullias

(74) *Attorney, Agent, or Firm* — Honigman LLP; Brett A. Krueger; Grant Griffith

(57) ABSTRACT

A transformer-transducer model for unifying streaming and non-streaming speech recognition includes an audio encoder, a label encoder, and a joint network. The audio encoder receives a sequence of acoustic frames, and generates, at each of a plurality of time steps, a higher order feature representation for a corresponding acoustic frame. The label encoder receives a sequence of non-blank symbols output by a final softmax layer, and generates, at each of the plurality of time steps, a dense representation. The joint network receives the higher order feature representation and the dense representation at each of the plurality of time steps, and generates a probability distribution over possible speech recognition hypothesis. The audio encoder of the model further includes a neural network having an initial stack of transformer layers trained with zero look ahead audio context, and a final stack of transformer layers trained with a variable look ahead audio context.

18 Claims, 7 Drawing Sheets



Related U.S. Application Data

(60) Provisional application No. 63/087,817, filed on Oct. 5, 2020.

(51) **Int. Cl.**

G06N 3/088	(2023.01)
G10L 15/06	(2013.01)
G10L 15/197	(2013.01)
G10L 15/22	(2006.01)
G10L 15/30	(2013.01)

(52) **U.S. Cl.**
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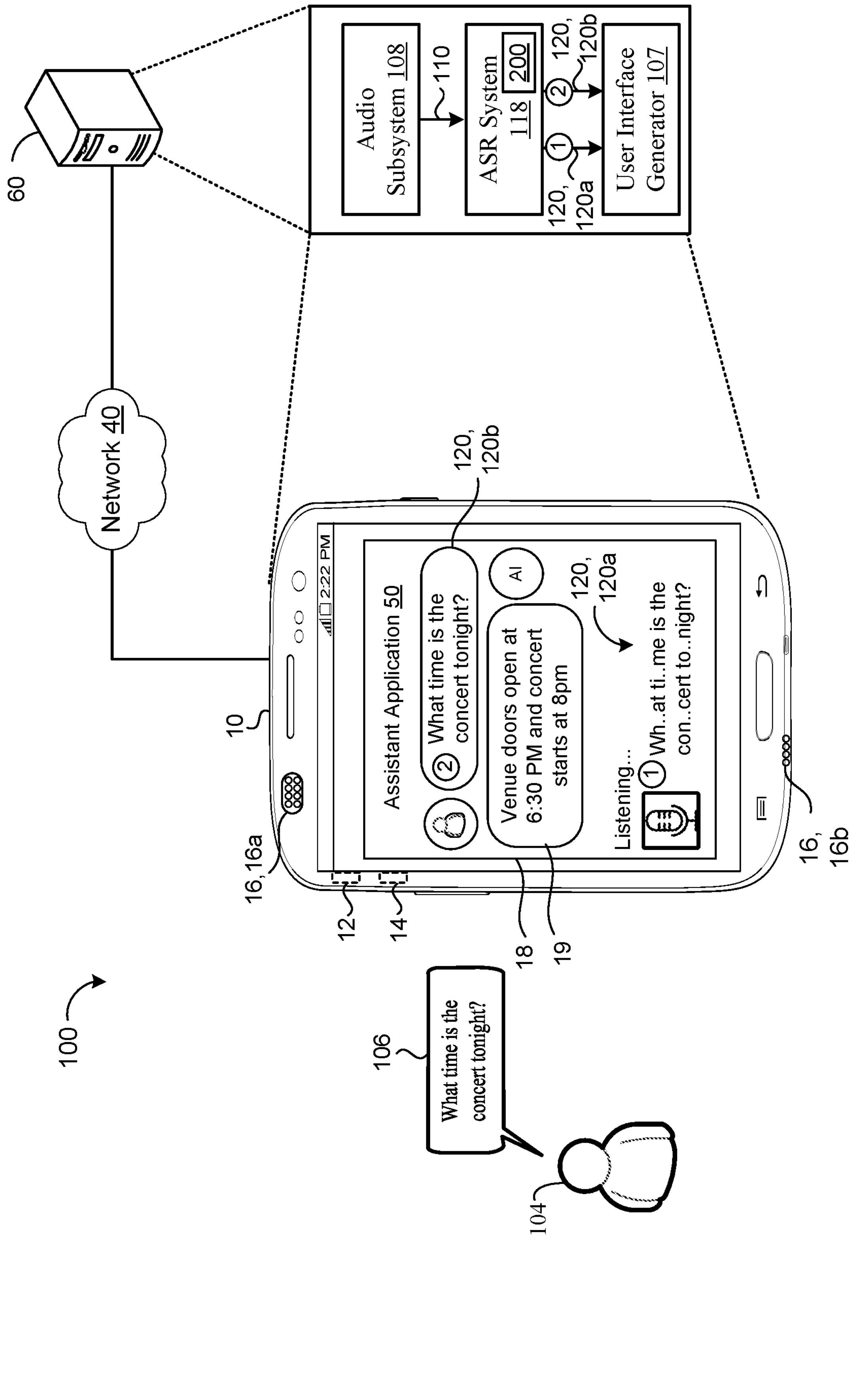
100
104
106
What time is the concert tonight?
10
12
14
16,16a
16, 16b
18
19
2:22 PM
Assistant Application 50
2 What time is the concert tonight?
AI
Venue doors open at 6:30 PM and concert starts at 8pm
120, 120b
120, 120a
Listening...
1 Wh..at ti..me is the con..cert to..night?
Network 40
60
Audio Subsystem 108
110
ASR System 118 200
120, 120a
120, 120b
User Interface Generator 107

FIG. 1

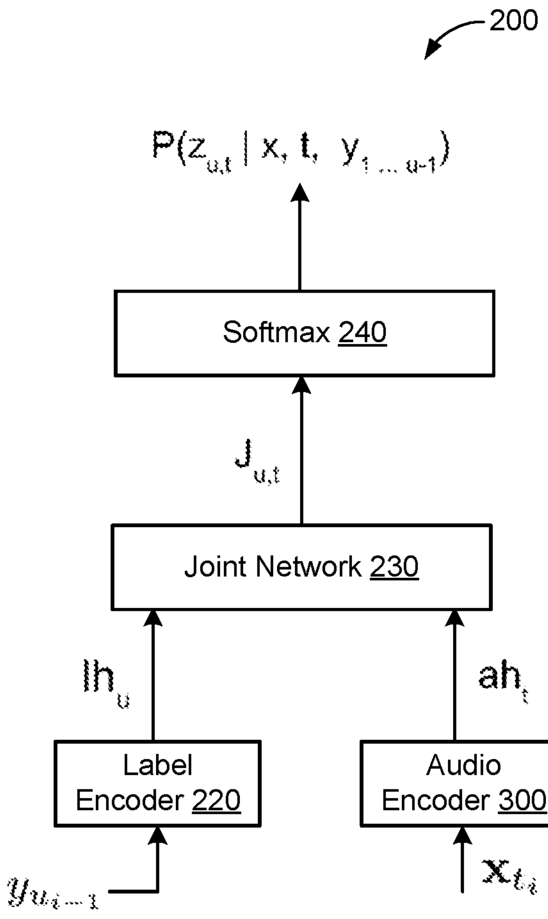
200
$P(z_{u,t} | x, t, y_{1 \ldots u-1})$
Softmax 240
$J_{u,t}$
Joint Network 230
lh_u
ah_t
Label Encoder 220
Audio Encoder 300
$y_{u_{i-1}}$
x_{t_i}

FIG. 2

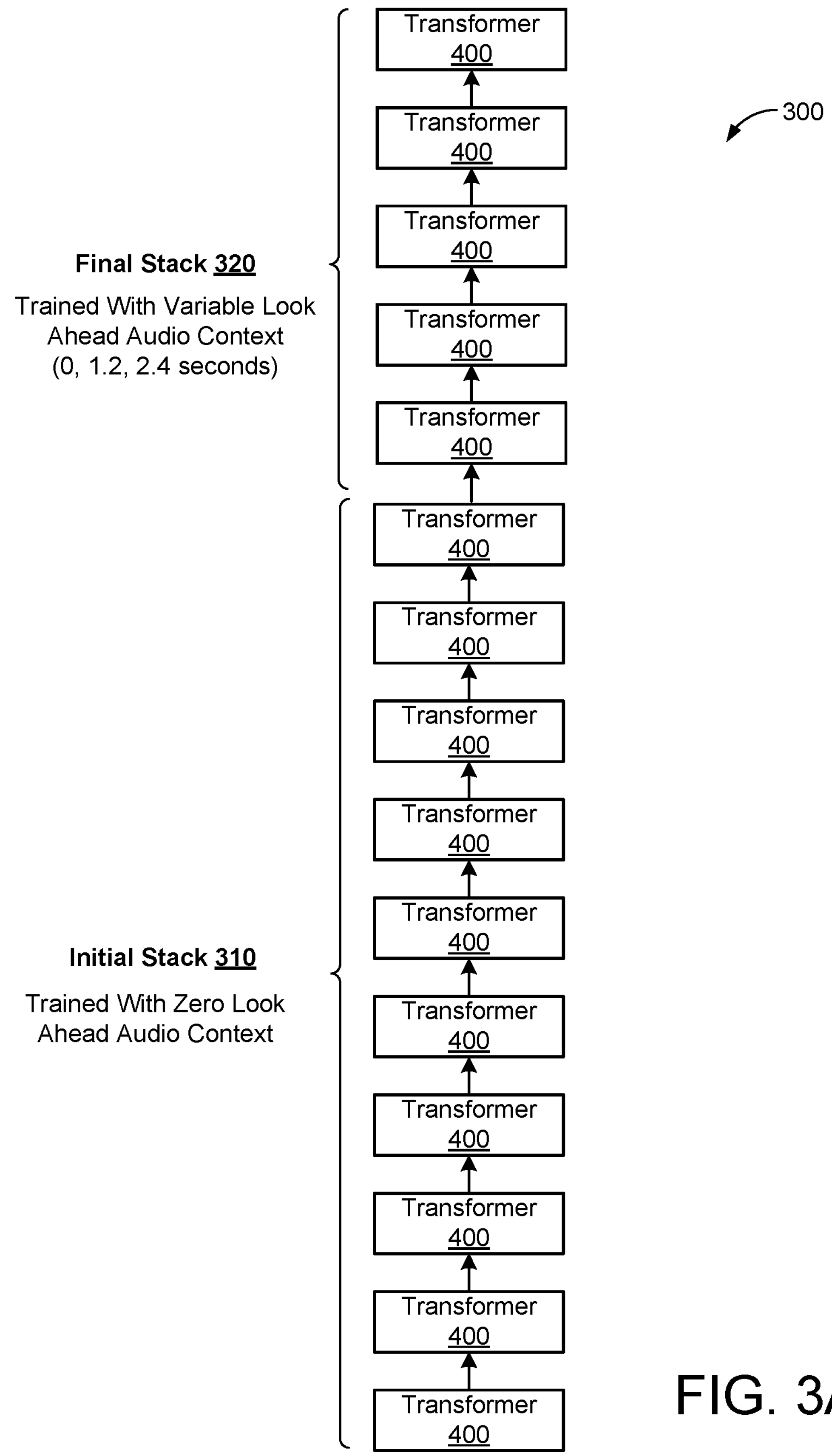
Transformer 400
Transformer 400
Transformer 400
Transformer 400
Transformer 400
Transformer 400
Transformer 400
Transformer 400
Transformer 400
Transformer 400
Transformer 400
Transformer 400
Transformer 400
Transformer 400
Transformer 400
300
Final Stack 320
Trained With Variable Look Ahead Audio Context (0, 1.2, 2.4 seconds)
Initial Stack 310
Trained With Zero Look Ahead Audio Context

FIG. 3A

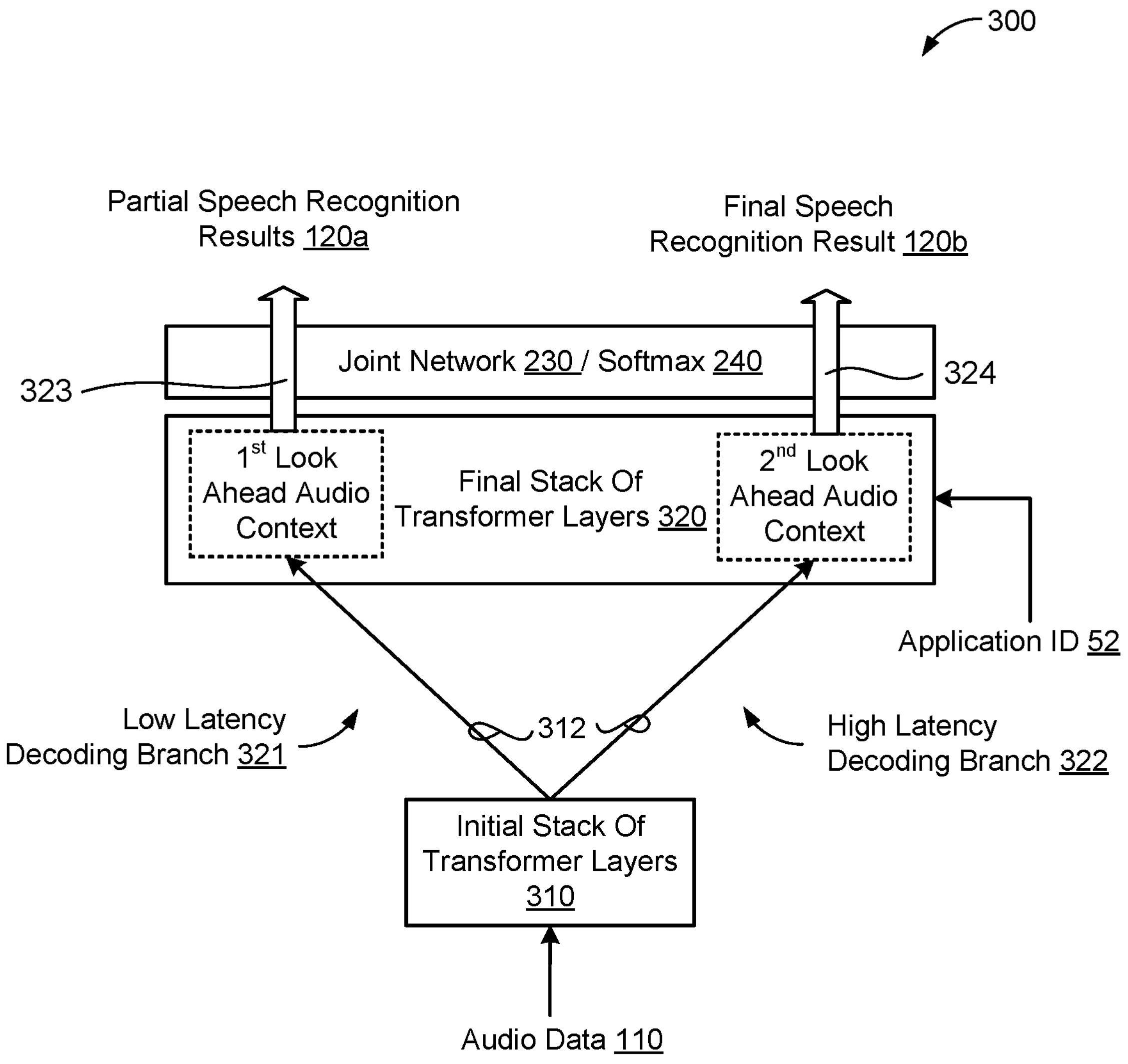
300
Partial Speech Recognition Results 120a
Final Speech Recognition Result 120b
Joint Network 230 / Softmax 240
323
324
1st Look Ahead Audio Context
Final Stack Of Transformer Layers 320
2nd Look Ahead Audio Context
Application ID 52
Low Latency Decoding Branch 321
312
High Latency Decoding Branch 322
Initial Stack Of Transformer Layers 310
Audio Data 110

FIG. 3B

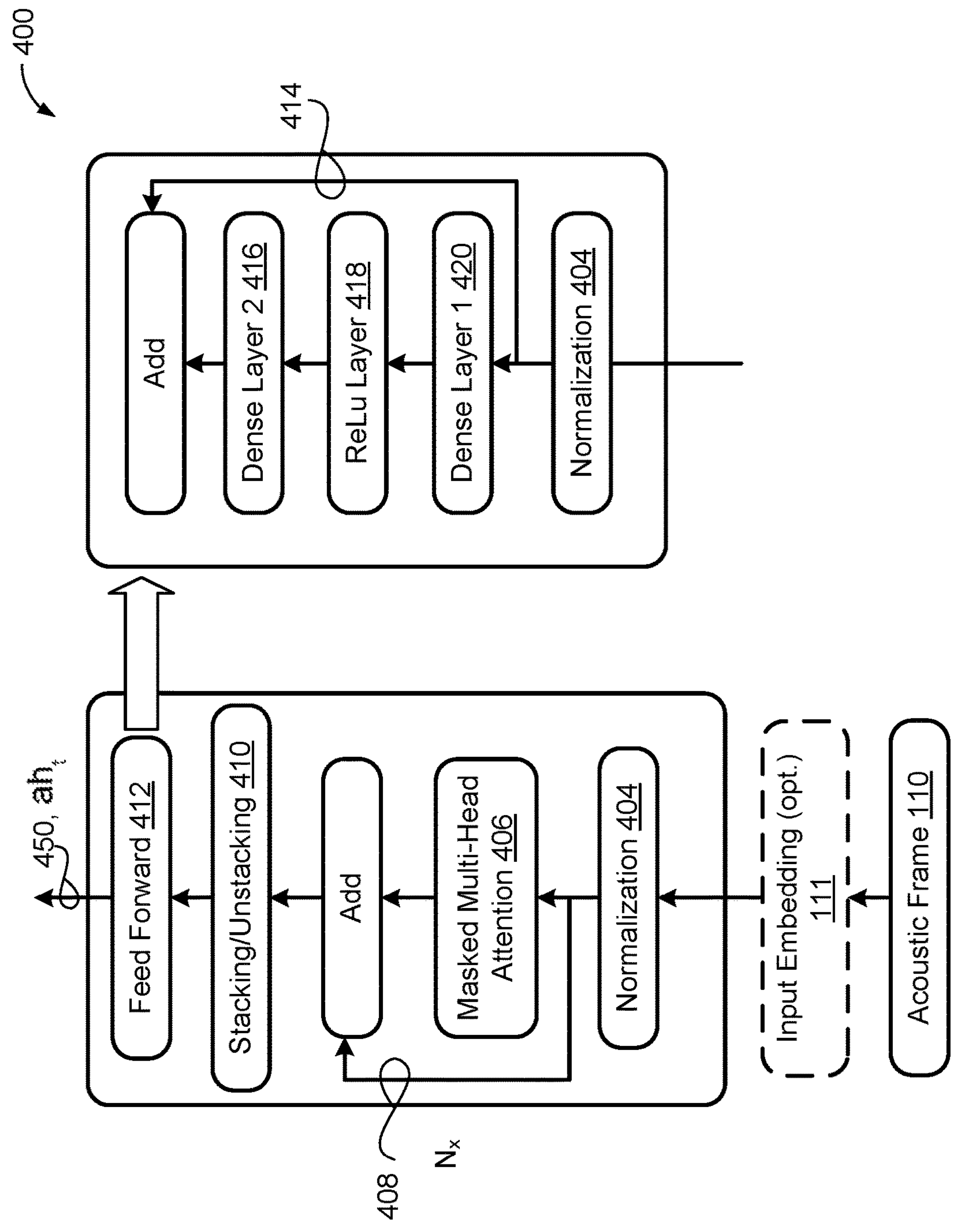
400
414
Add
Dense Layer 2 416
ReLu Layer 418
Dense Layer 1 420
Normalization 404
450, ah_τ
Feed Forward 412
Stacking/Unstacking 410
Add
Masked Multi-Head Attention 406
Normalization 404
Input Embedding (opt.) 111
Acoustic Frame 110
408
N_x

FIG. 4

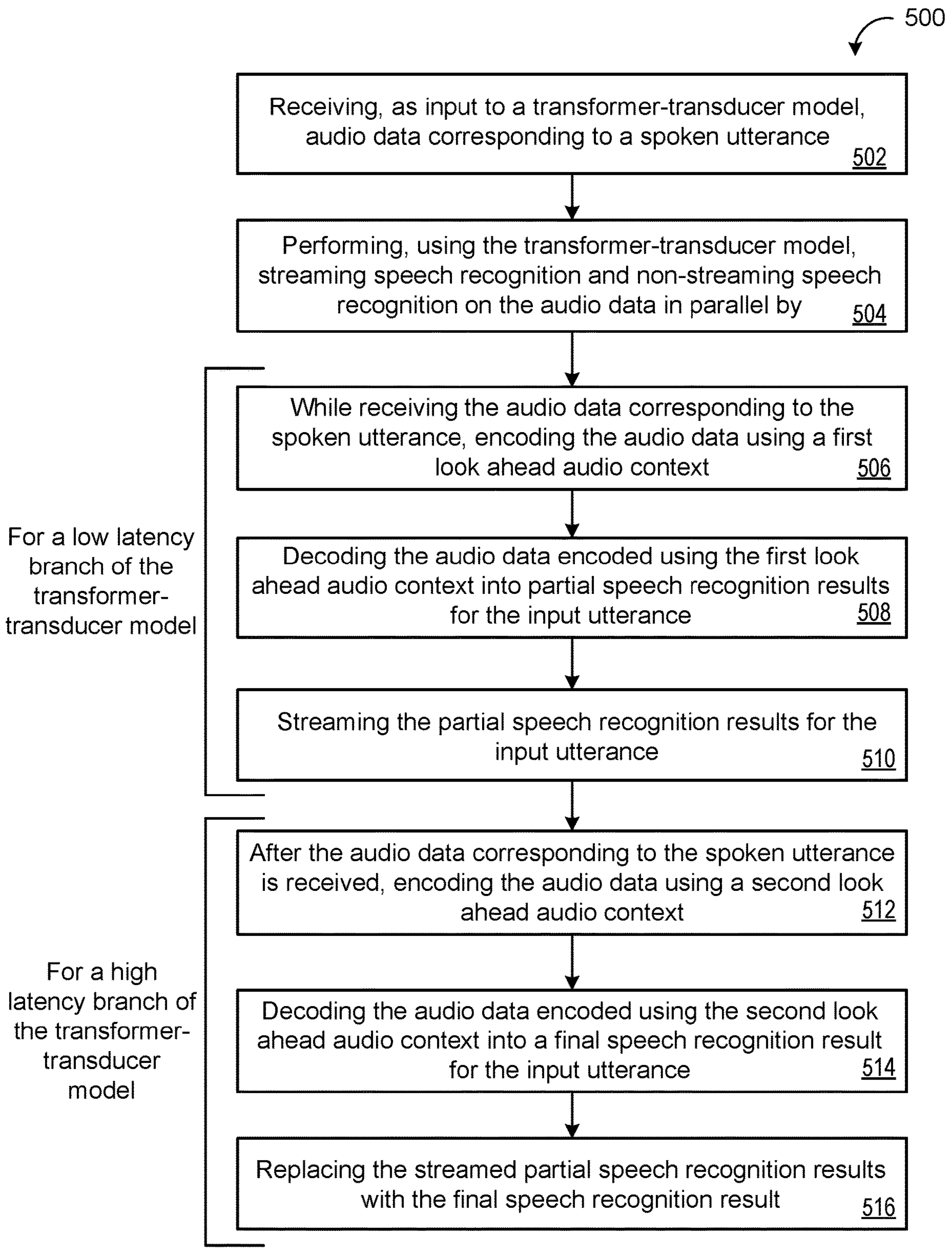
500
Receiving, as input to a transformer-transducer model, audio data corresponding to a spoken utterance 502
Performing, using the transformer-transducer model, streaming speech recognition and non-streaming speech recognition on the audio data in parallel by 504
For a low latency branch of the transformer-transducer model
While receiving the audio data corresponding to the spoken utterance, encoding the audio data using a first look ahead audio context 506
Decoding the audio data encoded using the first look ahead audio context into partial speech recognition results for the input utterance 508
Streaming the partial speech recognition results for the input utterance 510
For a high latency branch of the transformer-transducer model
After the audio data corresponding to the spoken utterance is received, encoding the audio data using a second look ahead audio context 512
Decoding the audio data encoded using the second look ahead audio context into a final speech recognition result for the input utterance 514
Replacing the streamed partial speech recognition results with the final speech recognition result 516

FIG. 5

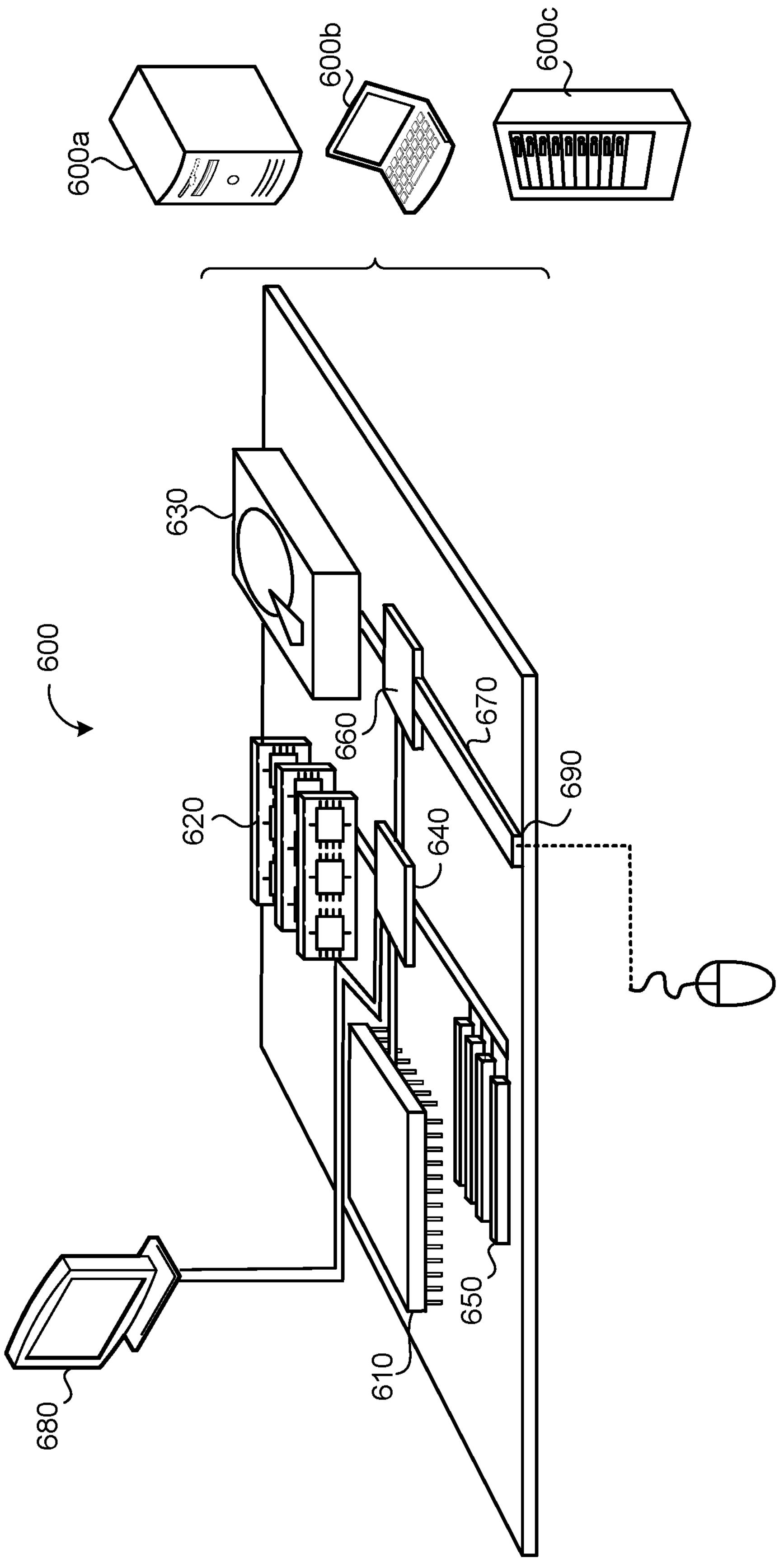

FIG. 6

ONE MODEL UNIFYING STREAMING AND NON-STREAMING SPEECH RECOGNITION

CROSS REFERENCE TO RELATED APPLICATIONS

This patent application is a continuation of, and claims priority under 35 U.S.C. § 120 from, U.S. patent application Ser. No. 17/210,465, filed on Mar. 23, 2021, which claims priority under 35 U.S.C. § 119(e) to U.S. Provisional Application 63/087,817, filed on Oct. 5, 2020. The disclosures of these prior applications are considered part of the disclosure of this application and are hereby incorporated by reference in their entireties.

TECHNICAL FIELD

This disclosure relates to using a unified model for streaming and non-streaming speech recognition.

BACKGROUND

Automatic speech recognition (ASR), the process of taking an audio input and transcribing it into text, has greatly been an important technology that is used in mobile devices and other devices. In general, ASR attempts to provide accurate transcriptions of what a person has said by taking an audio input (e.g., speech utterance) and transcribing the audio input into text. Modern ASR models continue to improve in both accuracy (e.g. a low word error rate (WER)) and latency (e.g., delay between the user speaking and the transcription) based on the ongoing development of deep neural networks. When using an ASR system today there is a demand that the ASR system decodes utterances in a streaming fashion that corresponds to real-time or even faster than real-time, but is also accurate. However, one challenge in developing deep learning-based ASR models is that while streaming models are low latency, they can be inaccurate. Conversely, non-streaming models are associated with high latency, but are generally offer higher accuracy.

SUMMARY

One aspect of the present disclosure provides a single transformer-transducer model for unifying streaming and non-streaming speech recognition. The single transformer-transducer model includes an audio encoder, a label encoder, and a joint network. The audio encoder is configured to receive, as input, a sequence of acoustic frames, and generate, at each of a plurality of time steps, a higher order feature representation for a corresponding acoustic frame in the sequence of acoustic frames. The label encoder is configured to receive, as input, a sequence of non-blank symbols output by a final softmax layer, and generate, at each of the plurality of time steps, a dense representation. The joint network is configured to receive, as input, the higher order feature representation generated by the audio encoder and the dense representation generated by the label encoder at each of the plurality of time steps, and generate, at each of the plurality of time steps, a probability distribution over possible speech recognition hypothesis at the corresponding time step. The audio encoder of the model further includes a neural network having a plurality of transformer layers. The plurality of transformer layers includes an initial stack of transformer layers each trained with zero look ahead audio context, and a final stack of transformer layers each trained with a variable look ahead audio context.

Implementations of the disclosure may include one or more of the following optional features. In some implementations, each transformer layer of the audio encoder includes a normalization layer, a masked multi-head attention layer with relative position encoding, residual connections, a stacking/unstacking layer, and a feedforward layer. In these implementations, the stacking/unstacking layer may be configured to change a frame rate of the corresponding transformer layer to adjust processing time by the single transformer-transducer model during training and inference. In some examples, the initial stack of transformer layers includes more transformer layers than the final stack of transformer layers. In some examples, during training, the variable look ahead audio context is uniformly sampled for each transformer layer in the final stack of transformer layers.

In some implementations, the model further includes a low latency decoding branch configured to decode corresponding speech recognition results for an input utterance from audio data encoded using a first look ahead audio context, and a high latency decoding branch configured to decode corresponding speech recognition results for the input utterance from audio data encoded using a second look ahead audio context. Here, the second look ahead audio context includes a longer duration of look ahead audio than the first look ahead audio context. In these implementations, the initial stack of transformer layers may apply zero look ahead audio context to compute shared activations for use by both the low latency decoding branch and the high latency decoding branch, the final stack of transformer layers may apply the first look ahead audio context to compute low latency activations for use by the low latency decoding branch and not the high latency decoding branch, and the final stack of transformer layers may apply the second look ahead audio context to compute high latency activations for use by the high latency decoding branch and not the low latency decoding branch. In some additional implementations, first look ahead audio context includes zero look ahead audio context.

In some examples, the low latency decoding branch and the high latency decoding branch execute in parallel for decoding the corresponding speech recognition results for the input utterance. In these examples, the corresponding speech recognition results decoded by the high latency decoding branch for the input utterance are delayed from the corresponding speech recognition results decoded by the low latency decoding branch for the input utterance by a duration based on a difference between the second look ahead audio context and the first look ahead audio context. Additionally or alternatively, the low latency decoding branch may be configured to stream the corresponding speech recognition results as partial speech recognition results as the input utterance is received by the single transformer-transducer model, and the high latency decoding branch may be configured to output the corresponding speech recognition results as a final transcription after the single transformer-transducer model receives the complete input utterance.

In some implementations, the input utterance is directed toward an application, and a duration of the second look ahead audio context used by the high latency decoding branch to decode the corresponding speech recognition results for the input utterance is based on a type of the application the input utterance is directed toward. In some

examples, the label encoder includes a neural network having a plurality of transformer layers. Alternatively, the label encoder may include a bigram embedding lookup decoder model. The single transformer-transducer model may execute on a client device or on a server-based system.

Another aspect of the present disclosure provides a computer-implemented method when executed on data processing hardware causes the data processing to perform operations that include receiving, as input to a transformer-transducer model, audio data corresponding to a spoken utterance, and performing, using the transformer-transducer model, streaming speech recognition and non-streaming speech recognition on the audio data in parallel. For a low latency branch of the transformer-transducer model, the operations also include, while receiving the audio data corresponding to the spoken utterance, encoding the audio data using a first look ahead audio context, decoding the audio data encoded using the first look ahead audio context into partial speech recognition results for the input utterance, and streaming the partial speech recognition results for the input utterance. For a high latency branch of the transformer-transducer model, the operations include, after the audio data corresponding to the spoken utterance is received, encoding the audio data using a second look ahead audio context, decoding the audio data encoded using the second look ahead audio context into a final speech recognition result for the input utterance, and replacing the streamed partial speech recognition results with the final speech recognition result.

This aspect may include one or more of the following optional features. In some implementations, the operations further include an audio encoder including a neural network having a plurality of transformer layers. The plurality of transformer layers includes an initial stack of transformer layers each trained with zero look ahead audio context, and a final stack of transformer layers each trained with a variable look ahead audio context. Each transformer layer may include a normalization layer, a masked multi-head attention layer with relative position encoding, residual connections, a stacking/unstacking layer, and a feedforward layer. Here, stacking/unstacking layer may be configured to change a frame rate of the corresponding transformer layer to adjust processing time by the single transformer-transducer model during training and inference.

In some examples, the initial stack of transformer layers includes more transformer layers than the final stack of transformer layers. In some implementations, during training, the variable look ahead audio context is uniformly sampled for each transformer layer in the final stack of transformer layers. In some examples, the initial stack of transformer layers apply zero look ahead audio context to compute shared activations for use by both the low latency branch and the high latency branch, the final stack of transformer layers apply the first look ahead audio context to compute low latency activations for use by the low latency branch and not the high latency decoding branch, and the final stack of transformer layers apply the second look ahead audio context to compute high latency activations for use by the high latency branch and not the low latency branch. The first look ahead audio context may include zero look ahead audio context. In some implementations, the final speech recognition results decoded by the high latency branch for the input utterance is delayed from the partial speech recognition results decoded by the low latency branch for the input utterance by a duration based on a difference between the second look ahead audio context and the first look ahead audio context.

In some examples, the operations further include receiving an application identifier indicating a type of application the input utterance is directed toward, and setting a duration of the second look ahead audio context based on the application identifier. In some implementations, transformer-transducer model includes a label encoder including a neural network having a plurality of transformer layers. In some examples, the transformer-transducer model includes a label encoder including a bigram embedding lookup decoder model. The data processing hardware executes on the transformer-transducer model and resides on either a client device or a server-based system.

The details of one or more implementations of the disclosure are set forth in the accompanying drawings and the description below. Other aspects, features, and advantages will be apparent from the description and drawings, and from the claims.

DESCRIPTION OF DRAWINGS

FIG. **1** is a schematic view of a speech environment implementing a single transformer-transducer model to perform streaming and non-streaming speech recognition.

FIG. **2** is a schematic view of an example transducer-transformer model architecture.

FIG. **3**A is a schematic view of an audio encoder including a plurality of transformer layers.

FIG. **3**B is a schematic view of an audio encoder arranged in a y-architecture to provide parallel low and high latency decoding branches.

FIG. **4** is a schematic view of an example transformer architecture.

FIG. **5** is flowchart of an example arrangement of operations for a method of unifying streaming and non-streaming speech recognition using the transformer-transducer model of FIG. **1**.

FIG. **6** is a schematic view of an example computing device that may be used to implement the systems and methods described herein.

Like reference symbols in the various drawings indicate like elements.

DETAILED DESCRIPTION

Automatic speech recognition (ASR) systems focus on providing not only quality/accuracy (e.g., low word error rates (WERs)), but also low latency (e.g., a short delay between the user speaking and a transcription appearing). Recently, end-to-end (E2E) ASR models have gained popularity in achieving state-of-the-art performance in accuracy and latency. In contrast to conventional hybrid ASR systems that include separate acoustic, pronunciation, and language models, E2E models apply a sequence-to-sequence approach to jointly learn acoustic and language modeling in a single neural network that is trained end to end from training data, e.g., utterance-transcription pairs. Here, an E2E model refers to a model whose architecture is constructed entirely of a neural network. A full neural network functions without external and/or manually designed components (e.g., finite state transducers, a lexicon, or text normalization modules). Additionally, when training E2E models, these models generally do not require bootstrapping from decision trees or time alignments from a separate system.

Examples of sequence-to-sequence models include "attention-based" models and "listen-attend-spell" (LAS) models. An LAS model transcribes speech utterances into characters using a listener component, an attender component, and a speller component. Here, the listener is a recurrent neural network (RNN) encoder that receives an audio input (e.g., a time-frequency representation of speech input) and maps the audio input to a higher-level feature representation. The attender attends to the higher-level feature to learn an alignment between input features and predicted sub word units (e.g., a grapheme or a wordpiece). The speller is an attention-based RNN decoder that generates character sequences from the input by producing a probability distribution over a set of hypothesized words. As attention-based models such as the LAS model generally process an entire sequence (e.g., audio waveform) and use the audio context for the entire sentence before generating an output (e.g., a sentence) based thereon, these models provide the output as a non-streaming transcription.

Moreover, when using an ASR system today there may be a demand for the ASR system to decode utterances in a streaming fashion that corresponds to displaying a description of an utterance in real time, or even faster than real-time, as a user speaks. To illustrate, when an ASR system is displayed on a user computing device, e.g., such as a mobile phone, that experiences direct user interactivity, an application (e.g., a digital assistant application), executing on the user device and using the ASR system, may require the speech recognition to be streaming such that words, word pieces, and/or individual characters appear on the screen as soon as they are spoken. Additionally, it is also likely that the user of the user device has a low tolerance for latency. For instance, when the user speaks a query requesting the digital assistant to retrieve details from a calendar application for an upcoming appointment, the user would like the digital assistant to provide a response conveying the retrieved details as quickly as possible. Due to this low tolerance, the ASR system strives to run on the user device in a manner that minimizes an impact from latency and inaccuracy that may detrimentally affect the user's experience. However, attention-based sequence-to-sequence models such as the LAS model that function by reviewing an entire input sequence of audio before generating output text, do not allow for streaming outputs as inputs are received. Due to this deficiency, deploying attention-based sequence-to-sequence models for speech applications that are latency sensitive and/or require real-time voice transcription may pose issues. This makes an LAS model alone not an ideal model for latency-sensitive applications and/or applications providing streaming transcription capabilities in real-time as a user speaks.

Another form of a sequence-to-sequence model known as a recurrent neural network transducer (RNN-T) does not employ an attention mechanism and, unlike other sequence-to-sequence models that generally need to process an entire sequence (e.g., audio waveform) to produce an output (e.g., a sentence), the RNN-T continuously processes input samples and streams output symbols, a feature that is particularly attractive for real-time communication. For instance, speech recognition with an RNN-T may output characters one-by-one as spoken. Here, an RNN-T uses a feedback loop that feeds symbols predicted by the model back into itself to predict the next symbols. Because decoding the RNN-T includes a beam search through a single neural network instead of a large decoder graph, an RNN-T may scale to a fraction of the size of a server-based speech recognition model. With the size reduction, the RNN-T may be deployed entirely on-device and be able to run offline (i.e., without a network connection); therefore, avoiding unreliability issues with communication networks.

Due to their inability to apply look ahead audio context (e.g., right context) when predicting recognition results, RNN-T models still lag behind large state-of-the-art conventional models (e.g., a server-based model with separate AM, PM, and LMs)) and attention-based sequence-to-sequence models (e.g., LAS model) in terms of quality (e.g., speech recognition accuracy as often measured by word error rate (WER)). To compensate for these lags in speech recognition accuracy, there has been a recent focus on developing a two-pass recognition system that includes a first-pass component of an RNN-T network followed by a second-pass component of a LAS network for rescoring recognition results generated during the first pass. With this design, the two-pass model benefits from the streaming nature of an RNN-T model with low latency while improving the accuracy of the RNN-T model through the second-pass incorporating the LAS network. Although the LAS network increases the latency when compared to only a RNN-T model, the increase in latency is considered reasonably slight and complies with latency constraints for on-device operation.

While suitable for providing streaming transcription capabilities, as well as latency-sensitive applications, that generally recognize conversational queries (e.g., set a timer", "remind me to buy the milk", etc.), RNN-T models leveraging Long Short-Term Memory (LSTM) to provide a sequence encoder have limited ability to look ahead audio context, and thereby become prone to deleting words when recognizing long-form speech. As used herein, long-form speech include non-conversational queries such as dictation-based queries where the user speaks to dictate an email, a message, document, social media post, or other piece of content.

Often, a user will employ a streaming speech recognition model, such as the RNN-T model, for recognizing conversational queries and a separate non-streaming speech recognition model for recognizing non-conversation queries. Typically, the application the user is directing his/her speech toward can be used to identify which one of the streaming or non-streaming speech recognition model to use for speech recognition. Requiring different and separate speech recognition models for performing speech recognition depending on the application and/or query type is computationally expensive and requires sufficient memory capacity for storing the respective models on the user device. Even if one of the models is executable on a remote server, additional costs for connecting to the remote server and bandwidth constraints can impact speech recognition performance, and ultimately, user experience.

Implementations herein are directed toward a single transformer-transducer (T-T) model for unifying streaming and non-streaming speech recognition tasks. As will become apparent, the T-T model may provide the positive attributes of RNN-T models such as streaming transcription capability, low latency speech recognition, small computational footprint, and low memory requirements, without suffering the aforementioned drawbacks of RNN-T models. That is, the T-T model may be trained on variable look ahead audio context so that a sufficient duration of look ahead audio context can be applied when performing speech recognition on an input utterance. Additionally, the T-T model may implement a y-architecture to provide a low latency branch for decoding streaming partial speech recognition results for an input utterance and a high latency branch for decoding a final speech recognition result for the same input utterance in parallel.

FIG. **1** is an example of a speech environment **100**. In the speech environment **100**, a user's **104** manner of interacting with a computing device, such as a user device **10**, may be through voice input. The user device **10** (also referred to generally as a device **10**) is configured to capture sounds (e.g., streaming audio data) from one or more users **104** within the speech environment **100**. Here, the streaming audio data may refer to a spoken utterance **106** by the user **104** that functions as an audible query, a command for the device **10**, or an audible communication captured by the device **10**. Speech-enabled systems of the device **10** may field the query or the command by answering the query and/or causing the command to be performed/fulfilled by one or more downstream applications.

The user device **10** may correspond to any computing device associated with a user **104** and capable of receiving audio data. Some examples of user devices **10** include, but are not limited to, mobile devices (e.g., mobile phones, tablets, laptops, etc.), computers, wearable devices (e.g., smart watches), smart appliances, internet of things (IoT) devices, vehicle infotainment systems, smart displays, smart speakers, etc. The user device **10** includes data processing hardware **12** and memory hardware **14** in communication with the data processing hardware **12** and stores instructions, that when executed by the data processing hardware **12**, cause the data processing hardware **12** to perform one or more operations. The user device **10** further includes an audio system **16** with an audio capture device (e.g., microphone) **16**, **16***a* for capturing and converting spoken utterances **106** within the speech environment **100** into electrical signals and a speech output device (e.g., a speaker) **16**, **16***b* for communicating an audible audio signal (e.g., as output audio data from the device **10**). While the user device **10** implements a single audio capture device **16***a* in the example shown, the user device **10** may implement an array of audio capture devices **16***a* without departing from the scope of the present disclosure, whereby one or more capture devices **16***a* in the array may not physically reside on the user device **10**, but be in communication with the audio system **16**.

In the speech environment **100**, an automated speech recognition (ASR) system **118** implementing a transformer-transducer (T-T) model **200** resides on the user device **10** of the user **104** and/or on a remote computing device **60** (e.g., one or more remote servers of a distributed system executing in a cloud-computing environment) in communication with the user device **10** via a network **40**. The user device **10** and/or the remote computing device **60** also includes an audio subsystem **108** configured to receive the utterance **106** spoken by the user **104** and captured by the audio capture device **16***a*, and convert the utterance **106** into a corresponding digital format associated with input acoustic frames **110** capable of being processed by the ASR system **118**. In the example shown, the user speaks a respective utterance **106** and the audio subsystem **108** converts the utterance **106** into corresponding audio data (e.g., acoustic frames) **110** for input to the ASR system **118**. Thereafter, the T-T model **200** receives, as input, the audio data **110** corresponding to the utterance **106**, and generates/predicts, as output, a corresponding transcription **120** (e.g., recognition result/hypothesis) of the utterance **106**. As described in greater detail below, the T-T model **200** may be trained with variable look ahead audio context to allow the T-T model **200** to set, during inference, different durations of look ahead audio context when performing speech recognition depending on how sensitive a query specified by the utterance **106** is to latency and/or how much tolerance the user **106** has for latency. For instance, a digital assistant application **50** executing on the user device **10** may require the speech recognition to be streaming such that words, word pieces, and/or individual characters appear on the screen as soon as they are spoken. Additionally, it is also likely that the user **104** of the user device **10** has a low tolerance for latency when issuing queries for the digital assistant application **50** to perform. In such scenarios when minimizing speech recognition latency is preferred, the T-T model **200** may apply zero or minimal look ahead audio context (also referred to as "right context") to provide streaming transcription capabilities in real-time as the user **104** is speaking the utterance **106**. On the other hand, when the user has a higher tolerance for speech recognition latency and/or the utterance **106** to be recognized is associated with long-form speech, the same T-T model **200** may apply a duration of look ahead audio context sufficient to provide an accurate transcription **120**, but incur increased latency based on the duration of look ahead audio context. Accordingly, the ASR system **118** may implement only a single T-T model **200** for a multitude of different speech recognition tasks to provide both streaming and non-streaming transcription capabilities without having to leverage separate ASR models on a task-by-task basis.

In some implementations, the T-T model **200** performs both streaming speech recognition and non-streaming speech recognition on the audio data **110** in parallel. For instance, in the example shown, the T-T model **200** performs, in parallel, streaming speech recognition on the audio data **110** using a first decoding branch (i.e., a low latency branch **321** (FIG. **3**B)) to produce partial speech recognition results **120**, **120***a*, and non-streaming speech recognition on the same audio data **110** using a second decoding branch (i.e., a high latency branch **322** (FIG. **3**B)) to produce a final speech recognition result **120**, **120***b*. Notably, the first decoding branch uses a first look ahead audio context that may be set to zero (or about 240 milliseconds) to produce the partial speech recognition results **120***a* while the second decoding branch may use a second look ahead audio context of a longer duration than the first look ahead audio context to produce the final speech recognition result **120***b*. Thus, the final speech recognition result **120***b* for the input utterance **106** may be delayed from the partial speech recognition results **120***a* for the input utterance by a duration based on a difference between the second look ahead audio context and the first look ahead audio context.

The user device **10** and/or the remote computing device **60** also executes a user interface generator **107** configured to present a representation of the transcription **120** of the utterance **106** to the user **104** of the user device **10**. As described in greater detail below, the user interface generator **107** may display the partial speech recognition results **120***a* in a streaming fashion during time **1** and subsequently display the final speech recognition result **120***b* during time **2**. In some configurations, the transcription **120** output from the ASR system **118** is processed, e.g., by a natural language understanding (NLU) module executing on the user device **10** or the remote computing device **60**, to execute a user command/query specified by the utterance **106**. Additionally or alternatively, a text-to-speech system (not shown) (e.g., executing on any combination of the user device **10** or the remote computing device **60**) may convert the transcription into synthesized speech for audible output by the user device **10** and/or another device.

In the example shown, the user **104** interacts with a program or application **50** (e.g., the digital assistant application **50**) of the user device **10** that uses the ASR system **118**. For instance, FIG. **1** depicts the user **104** communicating with the digital assistant application **50** and the digital assistant application **50** displaying a digital assistant interface **18** on a screen of the user device **10** to depict a conversation between the user and the digital assistant application **50**. In this example, the user **104** asks the digital assistant application **50**, "What time is the concert tonight?" This question from the user **104** is a spoken utterance **106** captured by the audio capture device **16***a* and processed by audio systems **16** of the user device **10**. In this example, the audio system **16** receives the spoken utterance **106** and converts it into acoustic frames **110** for input to the ASR system **118**.

Continuing with the example, the T-T model **200**, while receiving the acoustic frames **110** corresponding to the utterance **106** as the user **104** speaks, encodes the acoustic frames **110** using a first look ahead audio context and then decodes the encoded acoustic frames **110** using the first look ahead audio context into the partial speech recognition results **120***a*. During time **1**, the user interface generator **107** presents, via the digital assistant interface **18**, a representation of the partial speech recognition results **120***a* of the utterance **106** to the user **104** of the user device **10** in a streaming fashion such that words, word pieces, and/or individual characters appear on the screen as soon as they are spoken. In some examples, the first look ahead audio context is equal to zero.

In parallel, and after all of the acoustic frames **110** corresponding to the utterance **106** are received, the T-T model **200** encodes all of the acoustic frames **110** corresponding to the utterance **106** using a second look ahead audio context and then decodes the acoustic frames **110** using the second look ahead audio context into a final speech recognition result **120***b*. The duration of the second look ahead audio context may be 1.2 seconds, 2.4 seconds, or any other duration. In some examples, an indication such as an endpoint indicating that the user **104** has finished speaking the utterance **106** triggers the T-T model **200** to encode all the acoustic frames **110** using the second look ahead audio context. During time **2**, the user interface generator **107** presents, via the digital assistant interface **18**, a representation of the final speech recognition result **120***b* of the utterance **106** to the user **104** of the user device **10**. In some implementations, the user interface generator **107** replaces the representation of the partial speech recognition results **120***a* with the representation of the final speech recognition result **120***b*. For instance, as the final speech recognition result **120***b* is presumed to be more accurate than the partial speech recognition results **120***a* produced without leveraging look ahead audio context, the final speech recognition result **120***b* ultimately displayed as the transcription **120** may fix any terms that may have been misrecognized in the partial speech recognition results **120***a*. In this example, the streaming partial speech recognition results **120***a* output by the T-T model **200** and displayed on the screen of the user device at time **1** are associated with low latency and provide responsiveness to the user **104** that his/her query is being processed, while the final speech recognition result **120***b* output by the T-T model **200** and displayed on the screen at time **2** leverages look ahead audio context to improve the speech recognition quality in terms of accuracy, but at increased latency. However, since the partial speech recognition results **120***a* are displayed as the user speaks the utterance **106**, the higher latency associated with producing, and ultimately displaying the final recognition result is not noticeable to the user **104**.

In the example shown in FIG. **1**, the digital assistant application **50** may respond to the question posed by the user **10** using natural language processing. Natural language processing generally refers to a process of interpreting written language (e.g., the partial speech recognition results **120***a* and/or the final speech recognition result **120***b*) and determining whether the written language prompts any action. In this example, the digital assistant application **50** uses natural language processing to recognize that the question from the user **10** regards the user's schedule and more particularly a concert on the user's schedule. By recognizing these details with natural language processing, the automated assistant returns a response **19** to the user's query where the response **19** states, "Venue doors open at 6:30 PM and concert starts at 8 pm." In some configurations, natural language processing occurs on a remote server **60** in communication with the data processing hardware **12** of the user device **10**.

With reference to FIG. **2**, the T-T model **200** may provide an end-to-end (E2E) speech recognition by integrating acoustic, pronunciation, and language models into a single neural network, and does not require a lexicon or a separate text normalization component. Various structures and optimization mechanisms can provide increased accuracy and reduced model training time. The T-T model **200** includes a Transformer-Transducer (T-T) model architecture, which adheres to latency constraints associated with interactive applications. The T-T model **200** provides a small computational footprint and utilizes less memory requirements than conventional ASR architectures, making the T-T model architecture suitable for performing speech recognition entirely on the user device **10** (e.g., no communication with a remote server **60** is required). The T-T model **200** includes an audio encoder **300**, a label encoder **220**, and a joint network **230**. The audio encoder **300**, which is roughly analogous to an acoustic model (AM) in a traditional ASR system, includes a neural network having a plurality of transformer layers **400** (FIGS. **3**A, **3**B, and **4**). For instance, the audio encoder **300** reads a sequence of d-dimensional feature vectors (e.g., acoustic frames **110** (FIG. **1**)) $x=(x_1, x_2, \ldots, x_T)$, where $x_t \in \mathbb{R}_d$, and produces at each time step a higher-order feature representation. This higher-order feature representation is denoted as $ah_1, \ldots, ah_T$.

Similarly, the label encoder **220** may also include a neural network of transformer layers or a look-up table embedding model, which, like a language model (LM), processes the sequence of non-blank symbols output by a final Softmax layer **240** so far, $y_0, \ldots, y_{ui-1}$, into a dense representation Ih_u that encodes predicted label history. In implementations when the label encoder **220** includes the neural network of transformer layers, each transformer layer may include a normalization layer, a masked multi-head attention layer with relative position encoding, a residual connection, a feed forward layer, and a dropout layer. In these implementations, the label encoder **220** may include two transformer layers. In implementations when the label encoder **220** includes the look-up table embedding model with a bi-gram label context, the embedding model is configured to learn a weight vector of the d-dimension for each possible bigram label context, where d is the dimension of the outputs of the audio and label encoders **300**, **220**. In some examples, the total number of parameters in the embedding model is $N^2 \times d$ where N is the vocabulary size for the labels. Here, the learned weight vector is then used as the embedding of the bigram label context in the T-T model **200** to produce fast label encoder **220** runtimes.

Finally, with the T-T model architecture, the representations produced by the audio and label encoders **300**, **220** are combined by the joint network **230** using a dense layer $J_{u,t}$.

The joint network **230** then predicts $P(z_{u,t}|x, t, y_1, \ldots, y_{u-1})$, which is a distribution over the next output symbol. Stated differently, the joint network **230** generates, at each output step (e.g., time step), a probability distribution over possible speech recognition hypotheses. Here, the "possible speech recognition hypotheses" correspond to a set of output labels (also referred to as "speech units") each representing a grapheme (e.g., symbol/character) or a word piece in a specified natural language. For example, when the natural language is English, the set of output labels may include twenty-seven (27) symbols, e.g., one label for each of the 26-letters in the English alphabet and one label designating a space. Accordingly, the joint network **230** may output a set of values indicative of the likelihood of occurrence of each of a predetermined set of output labels. This set of values can be a vector (e.g., a one-hot vector) and can indicate a probability distribution over the set of output labels. In some cases, the output labels are graphemes (e.g., individual characters, and potentially punctuation and other symbols), but the set of output labels is not so limited. For example, the set of output labels can include wordpieces and/or entire words, in addition to or instead of graphemes. The output distribution of the joint network **230** can include a posterior probability value for each of the different output labels. Thus, if there are 100 different output labels representing different graphemes or other symbols, the output $z_{u,t}$ of the joint network **230** can include 100 different probability values, one for each output label. The probability distribution can then be used to select and assign scores to candidate orthographic elements (e.g., graphemes, wordpieces, and/or words) in a beam search process (e.g., by the Softmax layer **240**) for determining the transcription **120**.

The Softmax layer **240** may employ any technique to select the output label/symbol with the highest probability in the distribution as the next output symbol predicted by the T-T model **200** at the corresponding output step. In this manner, the T-T model **200** does not make a conditional independence assumption, rather the prediction of each symbol is conditioned not only on the acoustics but also on the sequence of labels output so far.

Referring to FIG. **3**A, in some implementations, the plurality of transformer layers **400** of the audio encoder **300** of the T-T model **200** includes an initial stack **310** of transformer layers **400** and a final stack **320** of transformer layers **400**. Each transformer layer **400** in the initial stack **310** may be trained with zero look ahead audio context, while each transformer layer **400** in the final stack **320** may be trained with variable look ahead audio context. The initial stack **310** of the T-T model **200** may have more transformer layers **400** than the final stack **320** of transformer layers **400**. For instance, the initial stack **310** of transformer layers **400** may include 15 transformer layers **400** while the final stack **320** of transformer layers **400** may include five (5) transformer layers **400**. However, the respective number of transformer layers **400** in each one of the initial stack **310** and final stack **320** is non-limiting. Accordingly, while examples herein may describe the initial stack **310** including 15 transformer layers **400** and the final stack **320** of transformer layers including five transformer layers **400**, the initial stack **310** of transformer layers **400** may include less than or more than 15 transformer layers **400**, and the final stack **320** of transformer layers **400** may include less than or more than five transformer layers **400**. Moreover, the total number of transformer layers **400** utilized by the audio encoder **300** may be less than or greater than 20 transformer layers **400**.

The T-T model **200** is trained on a training data set of audio data corresponding to spoken utterances paired with corresponding transcriptions. Training the T-T model **200** may include on the remote server **60** and the trained T-T model **200** may be pushed to the user device **10**. Training the final stack **320** of transformer layers **400** with variable look ahead audio context includes setting the left context of each transformer layer **400** in the final stack **320** constant and sampling a right context length of each layer in the final stack **320** from a given distribution in the training data set. Here, the sample right context length corresponds to a duration of the look ahead audio context sampled from the given distribution. As will become apparent, the sampled right context length designates a mask for self attention applied by a corresponding masked multi-head attention layer **406** (FIG. **4**) of each transformer layer **400** in the final stack **320**.

In some implementations, during training of the audio encoder **300**, the variable look ahead audio context is uniformly sampled for each transformer layer **400** in the final stack **320** of transformer layers **400**. For example, the variable look ahead audio context uniformly sampled for each transformer layer **400** in the final stack **320** of transformer layers **400** may include durations of zero, 1.2 seconds, and 2.4 seconds. These durations of look ahead audio context are non-limiting and may include different durations and/or sampling more or less than three different durations of look ahead audio context for the final stack **320** of transformer layers **400**. In these implementations during training, a respective look ahead context configuration for the transformer layers **400** may be specified for each different duration of look ahead audio context. Moreover, the audio encoder **300** of the T-T model **200** may be trained with an output delay of four acoustic frames **110**. For instance, continuing with the example above where the initial stack **310** of 15 transformer layers **400** is trained with no (zero) look ahead audio context and the final stack **320** of five transformer layers **400** is trained with variable look audio context, a first look ahead context configuration specified for zero look ahead audio context may include [0]×19+[4], a second look ahead context configuration specified for 1.2 seconds of look ahead audio context may include [0]×15+[8]×5, and a third look ahead audio context configuration specified for 2.4 seconds of look ahead audio context may include [0]×15+[16]×5. The number in brackets in each of the look ahead audio context configurations indicates a number of look ahead audio frames corresponding to the specified duration of look ahead audio context. In the example above, the first look ahead context configuration of [0]×19+[4] used for evaluating zero look ahead audio context indicates that the final transformer layer **400** applies an output delay of four audio frames **110**. Here, the output delay of four audio frames corresponds to 240 milliseconds of look ahead audio context.

In some additional implementations, rather than training the initial stack **310** of transformer layers **400** with zero look ahead audio context and only training the final stack **320** of transformer layers **400** with variable look ahead audio context, all of the transformer layers **400** of the audio encoder **300** of the T-T model **200** are trained with variable look ahead audio context. Continuing with the example above where the durations of zero, 1.2 seconds, and 2.4 seconds of look ahead context are uniformly sampled during training, a first look ahead context configuration specified for zero look ahead audio context may include [0]×19+[4] (e.g., where [4] specifies that the final transformer layer **400** applies the output delay of four audio frames corresponding to 240 milliseconds of look ahead audio context), a second look ahead context configuration specified for 1.2 seconds of look ahead audio context may include [2]×20, and a third look ahead audio context configuration specified for 2.4 seconds of look ahead audio context may include [4]×20. That is, the output delay of two [2] audio frames applied by each of the 20 transformer layers **400** evaluates a given distribution of the training data set for 1.2 seconds of look ahead audio context and the output delay of four [4] audio frames applied by each of the 20 transformer layers **400** evaluates another distribution of the training data set for 2.4 seconds of look ahead audio context.

FIG. **3**B illustrates an example of the T-T model **200** having the audio encoder **300** arranged in a y-architecture to enable the single T-T model **200** to perform, in parallel, streaming speech recognition and non-streaming speech recognition on an input utterance **106**. The y-architecture of the audio encoder **300** is formed by parallel low and high latency branches **321**, **322** that each extend from the initial stack **310** of transformer layers **400**. As described above with reference to FIG. **3**A, the initial stack **310** of transformer layers **400** may be trained with zero look ahead audio context and the final stack **320** of transformer layers **400** may be trained with variable look ahead audio context. Accordingly, during inference, the final stack **320** of transformer layers **400** may provide both: the low latency branch **321** (also referred to as 'low latency decoding branch **321**'), by applying a first look ahead audio context; and the high latency branch **322** (also referred to as 'high latency decoding branch **322**'), by applying a second look ahead audio context associated with a longer duration of look ahead audio context than the first look ahead audio context.

In some examples, the first look ahead audio context is zero or a minimal output delay (e.g., 240 milliseconds) to reduce word error rate loss due to constrained alignments applied during training. The second look ahead audio context may include any duration of look ahead audio context. For instance the second look ahead audio context may include a duration of 1.2 seconds or 2.4 seconds.

In the example shown, the initial stack **310** of transformer layers **400** of the audio encoder **300** receives the audio data **110** (e.g., acoustic frames) corresponding to the input utterance **106** spoken by the user **104** and captured by the user device **10**. While receiving the audio data **110**, the initial stack **310** of transformer layers **400** (e.g., 15 transformer layers **400**) may apply zero look ahead audio context to compute shared activations **312** for use by both the low latency branch **321** and the high latency branch **322**. Thereafter, and while receiving the audio data **110** as the user **104** is speaking the input utterance **106**, the final stack **320** of transformer layers **400** (e.g., five transformer layers **400**) uses the shared activations **312** computed by the initial stack **310** of transformer layers **400** and applies the first look ahead audio context to compute low latency activations **323** for use by the low latency branch **321** and not the high latency branch **322** that may be decoded via the joint network **230** and softmax **240** to provide partial speech recognition results **120***a* for the input utterance **106**. Accordingly, while receiving the audio data **110** corresponding to the input utterance **106**, the low latency branch **321** encodes the audio data **110** using the first look ahead audio context and decodes the encoded audio data **110** (i.e., represented by the low latency activations **323**) into the partial speech recognition results **120***a*. The partial speech recognition results **120***a* may be streamed in real-time for display on the user device **10** (FIG. **1**) as the input utterance **106** is spoken by the user **104**.

After the user **104** has completed speaking the input utterance **106** and all the audio data **110** is received, the final stack **320** of transformer layers **400** uses the shared activations **312** computed by the initial stack **310** of transformer layers **400** and applies the second look ahead audio context to compute high latency activations **324** for use by the high latency branch **322** and not the low latency branch **321** that may be decoded via the joint network **230** and softmax layer **240** to provide the final speech recognition result **120***b* for the input utterance **106**. Here, the final speech recognition result **120***b* decoded by the high latency branch **322** for the input utterance **106** is delayed from the partial speech recognition results **120***a* decoded by the low latency branch **321** by a duration based on a difference between the second look ahead audio context and the first look ahead audio context. Accordingly, after the audio data **110** corresponding to the input utterance **106** is received (e.g., the user **104** has completed speaking the utterance **106**), the high latency branch **322** encodes the audio data **110** using the second look ahead audio context and decodes the encoded audio data **110** (i.e., represented by the high latency activations **324**) into the final speech recognition result **120***b*. The final speech recognition result **120***b* may replace the streamed partial speech recognition results **120***a*. Notably, since the partial speech recognition results **120***a* may be streamed in real time, the user **104** may not perceive the latency incurred by the final speech recognition result **120***b*. Yet, the final speech recognition result **120***b* benefiting from look ahead audio context may correct any recognition errors present in the partial speech recognition result **120***a*, thereby rendering the final speech recognition result **120***b* more suitable for query interpretation by downstream NLU modules and/or applications. While not shown, a separate rescoring model (e.g., LAS model) may rescore candidate hypothesis decoded by the high latency decoding branch **322**.

In some examples, the duration of the second look ahead audio context is based on a type of application (e.g., digital assistant application **50**) the input utterance **106** is directed toward. For instance, the audio encoder **300** may receive an application identifier **52** indicating a type of application the input utterance is directed toward and the audio encoder may set the duration of the second look ahead audio context based on the application identifier **52**. The type of application the input utterance **106** is directed toward may serve as context information indicating the user's tolerance for speech recognition latency, speech recognition accuracy, whether the input utterance corresponds to a conversational query (e.g., short-form speech) or a non-conversational query (e.g., long-form speech such as dictation), or any other information that may be derived for use in optimizing/tuning the duration of second look ahead audio context applied.

FIG. **4** shows an example transformer layer **400** among the plurality of transformer layers of the audio encoder **300**. Here, during each time step, the initial transformer layer **400** receives a corresponding acoustic frame **110** as input and generates a corresponding output representation/embedding **450** received as input by the next transformer layer **400**. That is, each transformer layer **400** subsequent the initial transformer layer **400** may receive an input embedding **450** that corresponds to the output representation/embedding generated as output by the immediately preceding transformer layer **400**. The final transformer layer **400** (e.g., the last transformer layer in the final stack **320**) generates, at each of the plurality of time steps, the higher order feature representation ah_t (FIG. **2**) for the corresponding acoustic frame **110**.

The input to the label encoder **220** (FIG. **2**) may include a vector (e.g., a one-hot vector) indicating the sequence of non-blank symbols output by a final Softmax layer **240** so far, $y_0, \ldots, y_{ui-1}$. Accordingly, when the label encoder **220** includes transformer layers, the initial transformer layer may receive an input embedding **111** by passing the the one-hot vector through a look-up table.

Each transformer layer **400** of the audio encoder **300** includes a normalization layer **404**, a masked multi-head attention layer **406** with relative position encoding, residual connections **408**, a stacking/unstacking layer **410**, and a feedforward layer **412**. The masked multi-head attention layer **406** with relative position encoding provides a flexible way to control the amount (i.e., duration) of look ahead audio context that the T-T model **200** uses. Specifically, after the normalization layer **404** normalizes the acoustic frame **110** and/or input embedding **111**, the masked multi-head attention layer **406** projects the input to a value for all the heads. Thereafter, the masked multi-head layer **406** may mask an attention score to the left of the current acoustic frame **110** to produce an output conditioned only on the previous acoustic frames **110**. Then, weight-averaged values for all the heads are concatenated and passed to a dense layer 2 **416**, where a residual connection **414** is added to the normalized input and the output of the dense layer **416** to form the final output of the multi-head attention layer **406** with relative position encoding. The residual connections **408** are added to the output of the normalization layer **404** and are provided as inputs to a respective one of the masked multi-head attention layer **406** or the feedforward layer **412**. The stacking/unstacking layer **410** can be used to change a frame rate for each transformer layer **400** to speed up training and inference.

The feedforward layer **412** applies normalization layer **404**, followed by dense layer 1 **420**, rectified linear layer (ReLu) **418**, and dense layer 2 **416**. The ReLu **418** is used as the activation on the output of dense layer 1 **420**. Like in the multi-head attention layer **406** with relative position encoding, a residual connection **414** of the output from the normalized layer **404** is added to the output of the dense layer 2 **416**.

FIG. **5** includes a flowchart of an example arrangement of operations for a method **500** of unifying streaming and non-streaming speech recognition using a single transformer-transducer (T-T) model **200**. At operation **502**, the method **500** includes receiving, as input to a T-T model **200**, audio data **110** corresponding to a spoken utterance **106**. At operation **504**, the method further includes performing, using the T-T model **200**, streaming speech recognition and non-streaming speech recognition on the audio data **110** in parallel.

For a low latency branch **321** of the T-T model **200**, the method **500** includes, at operation **506**, while receiving the audio data **110** corresponding to the spoken utterance **106**, encoding the audio data **110** using a first look ahead audio context. The method **500** also includes, at operation **508**, decoding the audio data **110** encoded using the first look ahead audio context into partial speech recognition results **120***a* for the input utterance **106**. At operation **510**, the method **500** further includes streaming the partial speech recognition results **120***a* for the input utterance **106**.

For a high latency branch **322** of the T-T model **200**, the method **500** includes, at operation **512**, after the audio data **110** corresponding to the spoken utterance **106** is received, encoding the audio data **110** using a second look ahead audio context. The method **500** also includes, at operation **514**, decoding the audio data **110** encoded using the second look ahead audio context into a final speech recognition result **120***b* for the input utterance **106**. At operation **516**, the method **500** further includes replacing the streamed partial speech recognition results **120***a* with the final speech recognition result **120***b*.

FIG. **6** is schematic view of an example computing device **600** that may be used to implement the systems and methods described in this document. The computing device **600** is intended to represent various forms of digital computers, such as laptops, desktops, workstations, personal digital assistants, servers, blade servers, mainframes, and other appropriate computers. The components shown here, their connections and relationships, and their functions, are meant to be exemplary only, and are not meant to limit implementations of the inventions described and/or claimed in this document.

The computing device **600** includes a processor **610**, memory **620**, a storage device **630**, a high-speed interface/controller **640** connecting to the memory **620** and high-speed expansion ports **650**, and a low speed interface/controller **660** connecting to a low speed bus **670** and a storage device **630**. Each of the components **610**, **620**, **630**, **640**, **650**, and **660**, are interconnected using various busses, and may be mounted on a common motherboard or in other manners as appropriate. The processor **610** can process instructions for execution within the computing device **600**, including instructions stored in the memory **620** or on the storage device **630** to display graphical information for a graphical user interface (GUI) on an external input/output device, such as display **680** coupled to high speed interface **640**. In other implementations, multiple processors and/or multiple buses may be used, as appropriate, along with multiple memories and types of memory. Also, multiple computing devices **600** may be connected, with each device providing portions of the necessary operations (e.g., as a server bank, a group of blade servers, or a multi-processor system).

The memory **620** stores information non-transitorily within the computing device **600**. The memory **620** may be a computer-readable medium, a volatile memory unit(s), or non-volatile memory unit(s). The non-transitory memory **620** may be physical devices used to store programs (e.g., sequences of instructions) or data (e.g., program state information) on a temporary or permanent basis for use by the computing device **600**. Examples of non-volatile memory include, but are not limited to, flash memory and read-only memory (ROM)/programmable read-only memory (PROM)/erasable programmable read-only memory (EPROM)/electronically erasable programmable read-only memory (EEPROM) (e.g., typically used for firmware, such as boot programs). Examples of volatile memory include, but are not limited to, random access memory (RAM), dynamic random access memory (DRAM), static random access memory (SRAM), phase change memory (PCM) as well as disks or tapes.

The storage device **630** is capable of providing mass storage for the computing device **600**. In some implementations, the storage device **630** is a computer-readable medium. In various different implementations, the storage device **630** may be a floppy disk device, a hard disk device, an optical disk device, or a tape device, a flash memory or other similar solid state memory device, or an array of devices, including devices in a storage area network or other configurations. In additional implementations, a computer program product is tangibly embodied in an information carrier. The computer program product contains instructions that, when executed, perform one or more methods, such as those described above. The information carrier is a computer- or machine-readable medium, such as the memory **620**, the storage device **630**, or memory on processor **610**.

The high speed controller **640** manages bandwidth-intensive operations for the computing device **600**, while the low speed controller **660** manages lower bandwidth-intensive operations. Such allocation of duties is exemplary only. In some implementations, the high-speed controller **640** is coupled to the memory **620**, the display **680** (e.g., through a graphics processor or accelerator), and to the high-speed expansion ports **650**, which may accept various expansion cards (not shown). In some implementations, the low-speed controller **660** is coupled to the storage device **630** and a low-speed expansion port **690**. The low-speed expansion port **690**, which may include various communication ports (e.g., USB, Bluetooth, Ethernet, wireless Ethernet), may be coupled to one or more input/output devices, such as a keyboard, a pointing device, a scanner, or a networking device such as a switch or router, e.g., through a network adapter.

The computing device **600** may be implemented in a number of different forms, as shown in the figure. For example, it may be implemented as a standard server **600***a* or multiple times in a group of such servers **600***a*, as a laptop computer **600***b*, or as part of a rack server system **600***c*.

Various implementations of the systems and techniques described herein can be realized in digital electronic and/or optical circuitry, integrated circuitry, specially designed ASICs (application specific integrated circuits), computer hardware, firmware, software, and/or combinations thereof. These various implementations can include implementation in one or more computer programs that are executable and/or interpretable on a programmable system including at least one programmable processor, which may be special or general purpose, coupled to receive data and instructions from, and to transmit data and instructions to, a storage system, at least one input device, and at least one output device.

A software application (i.e., a software resource) may refer to computer software that causes a computing device to perform a task. In some examples, a software application may be referred to as an "application," an "app," or a "program." Example applications include, but are not limited to, system diagnostic applications, system management applications, system maintenance applications, word processing applications, spreadsheet applications, messaging applications, media streaming applications, social networking applications, and gaming applications.

The non-transitory memory may be physical devices used to store programs (e.g., sequences of instructions) or data (e.g., program state information) on a temporary or permanent basis for use by a computing device. The non-transitory memory may be volatile and/or non-volatile addressable semiconductor memory. Examples of non-volatile memory include, but are not limited to, flash memory and read-only memory (ROM)/programmable read-only memory (PROM)/erasable programmable read-only memory (EPROM)/electronically erasable programmable read-only memory (EEPROM) (e.g., typically used for firmware, such as boot programs). Examples of volatile memory include, but are not limited to, random access memory (RAM), dynamic random access memory (DRAM), static random access memory (SRAM), phase change memory (PCM) as well as disks or tapes.

These computer programs (also known as programs, software, software applications or code) include machine instructions for a programmable processor, and can be

implemented in a high-level procedural and/or object-oriented programming language, and/or in assembly/machine language. As used herein, the terms "machine-readable medium" and "computer-readable medium" refer to any computer program product, non-transitory computer readable medium, apparatus and/or device (e.g., magnetic discs, optical disks, memory, Programmable Logic Devices (PLDs)) used to provide machine instructions and/or data to a programmable processor, including a machine-readable medium that receives machine instructions as a machine-readable signal. The term "machine-readable signal" refers to any signal used to provide machine instructions and/or data to a programmable processor.

The processes and logic flows described in this specification can be performed by one or more programmable processors, also referred to as data processing hardware, executing one or more computer programs to perform functions by operating on input data and generating output. The processes and logic flows can also be performed by special purpose logic circuitry, e.g., an FPGA (field programmable gate array) or an ASIC (application specific integrated circuit). Processors suitable for the execution of a computer program include, by way of example, both general and special purpose microprocessors, and any one or more processors of any kind of digital computer. Generally, a processor will receive instructions and data from a read only memory or a random access memory or both. The essential elements of a computer are a processor for performing instructions and one or more memory devices for storing instructions and data. Generally, a computer will also include, or be operatively coupled to receive data from or transfer data to, or both, one or more mass storage devices for storing data, e.g., magnetic, magneto optical disks, or optical disks. However, a computer need not have such devices. Computer readable media suitable for storing computer program instructions and data include all forms of non-volatile memory, media and memory devices, including by way of example semiconductor memory devices, e.g., EPROM, EEPROM, and flash memory devices; magnetic disks, e.g., internal hard disks or removable disks; magneto optical disks; and CD ROM and DVD-ROM disks. The processor and the memory can be supplemented by, or incorporated in, special purpose logic circuitry.

To provide for interaction with a user, one or more aspects of the disclosure can be implemented on a computer having a display device, e.g., a CRT (cathode ray tube), LCD (liquid crystal display) monitor, or touch screen for displaying information to the user and optionally a keyboard and a pointing device, e.g., a mouse or a trackball, by which the user can provide input to the computer. Other kinds of devices can be used to provide interaction with a user as well; for example, feedback provided to the user can be any form of sensory feedback, e.g., visual feedback, auditory feedback, or tactile feedback; and input from the user can be received in any form, including acoustic, speech, or tactile input. In addition, a computer can interact with a user by sending documents to and receiving documents from a device that is used by the user; for example, by sending web pages to a web browser on a user's client device in response to requests received from the web browser.

A number of implementations have been described. Nevertheless, it will be understood that various modifications may be made without departing from the spirit and scope of the disclosure. Accordingly, other implementations are within the scope of the following claims.

What is claimed is:

1. A computer-implemented method executed on data processing hardware that causes the data processing hardware to perform operations comprising:
receiving audio data corresponding to a spoken utterance;
encoding, by an initial stack of multi-head attention layers, the audio data to compute shared activations:
while receiving the audio data corresponding to the spoken utterance:
encoding, by a final stack of multi-head attention layers while applying a first look ahead audio context, the shared activations to compute low latency activations; and
decoding the low latency activations into partial speech recognition results for the spoken utterance; and
after the audio data corresponding to the spoken utterance is received:
encoding, by the final stack of multi-head attention layers while applying a second look ahead audio context, the shared activations to compute high latency activations; and
decoding the high latency activations into a final speech recognition result for the spoken utterance,
wherein:
the initial stack of multi-head attention layers are trained with zero look ahead audio context; and
the final stack of multi-head attention layers are trained with variable look ahead audio context.

2. The computer-implemented method of claim 1, wherein the operations further comprise, while receiving the audio data corresponding to the spoken utterance, streaming the partial speech recognition results for the spoken utterance.

3. The computer-implemented method of claim 2, wherein the operations further comprise, after the audio data corresponding to the spoken utterance is received, replacing the streamed partial speech recognition results with the final speech recognition result.

4. The computer-implemented method of claim 1, wherein during training, the variable look ahead audio context is uniformly sampled for each multi-head attention layer in the final stack of multi-head attention layers.

5. The computer-implemented method of claim 1, wherein the initial stack of multi-head attention layers comprises more multi-head attention layers than the final stack of multi-head attention layers.

6. The computer-implemented method of claim 1, wherein the first look ahead audio context comprises zero look ahead audio context.

7. The computer-implemented method of claim 1, wherein a low latency decoding branch decodes the low latency activations into the partial speech recognition results for the spoken utterance in parallel with a high latency decoding branch decoding the high latency activations into the final speech recognition result for the spoken utterance.

8. The computer-implemented method of claim 1, wherein the final speech recognition result decoded from the shared activations is delayed from the partial speech recognition results decoded from the shared activations by a duration based on a difference between the second look ahead audio context and the first look ahead audio context.

9. The computer-implemented method of claim 1, wherein the operations further comprise:
receiving an application identifier indicating a type of application the spoken utterance is directed toward; and
setting a duration of the second look ahead audio context based on the application identifier.

10. A system comprising:
data processing hardware; and
memory hardware in communication with the data processing hardware and storing instructions that when executed by the data processing hardware cause the data processing hardware to perform operations comprising:
receiving audio data corresponding to a spoken utterance;
encoding, by an initial stack of multi-head attention layers, the audio data to compute shared activations:
while receiving the audio data corresponding to the spoken utterance:
encoding, by a final stack of multi-head attention layers while applying a first look ahead audio context, the shared activations to compute low latency activations; and
decoding the low latency activations into partial speech recognition results for the spoken utterance; and
after the audio data corresponding to the spoken utterance is received:
encoding, by the final stack of multi-head attention layers while applying a second look ahead audio context, the shared activations to compute high latency activations; and
decoding the high latency activations into a final speech recognition result for the spoken utterance,
wherein:
the initial stack of multi-head attention layers are trained with zero look ahead audio context; and
the final stack of multi-head attention layers are trained with variable look ahead audio context.

11. The system of claim 10, wherein the operations further comprise, while receiving the audio data corresponding to the spoken utterance, streaming the partial speech recognition results for the spoken utterance.

12. The system of claim 11, wherein the operations further comprise, after the audio data corresponding to the spoken utterance is received, replacing the streamed partial speech recognition results with the final speech recognition result.

13. The system of claim 10, wherein during training, the variable look ahead audio context is uniformly sampled for each multi-head attention layer in the final stack of multi-head attention layers.

14. The system of claim 10, wherein the initial stack of multi-head attention layers comprises more multi-head attention layers than the final stack of multi-head attention layers.

15. The system of claim 10, wherein the first look ahead audio context comprises zero look ahead audio context.

16. The system of claim 10, wherein a low latency decoding branch decodes the low latency activations into the partial speech recognition results for the spoken utterance in parallel with a high latency decoding branch decoding the high latency activations into the final speech recognition result for the spoken utterance.

17. The system of claim 10, wherein the final speech recognition result decoded from the shared activations is delayed from the partial speech recognition results decoded from the shared activations by a duration based on a difference between the second look ahead audio context and the first look ahead audio context.

18. The system of claim 10, wherein the operations further comprise:
receiving an application identifier indicating a type of application the spoken utterance is directed toward; and

setting a duration of the second look ahead audio context based on the application identifier.

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